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Coordinated Optimization of On-Load Tap Changers and Shunt Capacitor Banks Using Evolutionary and Swarm Intelligence Techniques for Voltage Stability Enhancement

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Abstract

The growing electricity demand and incorporation of the distributed energy resources have increased the burden of operations in the radial distribution networks. The instabilities in voltages and high power losses. The proposed study is based on a coordinated multi-objective optimization model to constrain the on-load tap changers (OLTCs) and shunt capacitor banks in parallel to optimize the voltage regulation and reduce system losses. IEEE 33-bus radial distribution system is taken as a standard and two sophisticated metaheuristic methods Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are applied to find optimal locations, sizes, and operating parameters of devices under the conventional voltage limitations (0.95 -1.05 p.u.).With base conditions, the system is characterized by a high level of performance degradation as 21 buses are exceeding the voltage limits with a minimum voltage of 0.9131 p.u. as well as by 202.7 kW of active and 135.1 kVAr of reactive power losses, respectively. The synchronized optimization plan is effective in reestablishing all bus voltages within allowable limits as well as minimizing active and reactive losses to 130.7 kW and 93.3 kVAr. Comparative analysis shows that coordinated control performs far better than individual deployment of OLTCs or capacitor banks showing better convergence behavior and near global optimum solutions.

The results substantiate the claim that the smartness of voltage regulation equipment application with the evolutionary and swarm intelligence methods can deliver a practical, scalable, and computationally economic technique concerning a higher voltage stability, lesser technical losses, and greater dependability of the operational characteristics of contemporary distributions.

Keywords: *Tap changer, Capacitor bank, Genetic algorithm, Voltage drop, IEEE voltage standards*

Introduction

The interface between generation and end users which directly affect the reliability of the services, quality of voltages, and efficiency of operation is the electric power distribution system. Yet, due to the large feeder impedance, and insufficient reactive power imbalance, radial distribution networks inherently tend to be susceptible to voltage drops and increased technical losses. The growing electricity consumption and the growing use of the renewable energy sources, which introduce unpredictability and variability to the operation of the systems add to these concerns.

These problems have been suggested to be addressed in various ways, such as adaptive control of on load tap changer (OLTCs), and assessment of voltage stability with indices such as L-index, a shunt capacitor compensation. Although these techniques have been observed to work well on their own, their application will often limit the overall performance of the system. In particular, they cannot minimize losses and regulate voltage at the same time within the same framework.

In order to address this shortcoming this paper develops the voltage drop and power loss reduction as a multi-objective optimization problem. The IEEE 33-bus radial system is a coordinated scheme in which OLTCs and shunt capacitor banks are involved in the control. Evolutionary and swarm intelligence methods are used to solve the optimization problems with the focus being laid on finding optimal locations of devices, their sizes, and operating parameters according to the system constraints.

The objective cost function , defined as:

$$\min J = \sum_{t=1}^{T} \left(P_{\text{loss}}(t) + \omega_1 \Delta V(t) + \omega_2 C_{\text{op}}(t) \right) \tag{1}$$

Where:

$$\Delta V(t) = \sum_{i=1}^{N} | V_i(t) - V_{ref} |$$

$V_{ref} = 1.0$ pu

$P_{\text{loss}}(t)$: Total active power loss at time step

$\Delta V(t)$: Aggregate voltage deviation from the nominal value

$C_{\text{op}}(t)$: Operating cost associated with OLTC and shunt capacitor switching

ω_1, ω_2 : Weighting coefficients reflecting the relative importance of voltage regulation and operational cost

$V_i(t)$: Voltage magnitude at bus at time

N : Total number of buses

T : Total number of time intervals

A Genetic Algorithm (GA) is used to solve the mixed integer nonlinear optimization. Each solution in GA is represented by a chromosome that represents control factors such as capacitor bank sizes, OLTC tap locations, and system operating parameters. The inverse of the objective function is used to assess each solution fitness.

Each chromosome is defined as a mixed-integer decision vector:

$$x = [\underbrace{T}_{\text{Tap Positions}}, \underbrace{Q_{cap}}_{\text{Capacitor Steps}}, \underbrace{V_g}_{\text{Generator Voltages}}, \underbrace{P_{ES}}_{\text{Energy Storage Dispatch}}]$$

The fitness of each chromosome is evaluated as:

$$\text{Fitness} = \frac{1}{1+J}$$

In addition, particle Swarm optimization (PSO) as shown in Figure1 is used due to its robust convergence properties and ease of use. PSO simulates the behaviors of a group of particles that iteratively change their positions in response to both individual and global optimal solutions [1]. The velocity updates formula can be written as follows [2]:

$$\mathrm{V_i(t+1) = W * V_i(t) + C_1 * r_1\left[P_{best_i} - X_i(t)\right] + C_2 * r_2[G_{best} - X_i(t)]} \tag{2}$$

Followed by position updates:

$$\mathrm{X\ (t+1) \quad X\ (t) + V\ (t+1)} \tag{3}$$

Here, (t) and(t) are the velocity and position of particle i at time t, W is the inertia weight, and are acceleration coefficients and and are random numbers between 0 and 1.

These optimization techniques make it possible to find near optimal solution for complex power system problems and to efficiently explore the search space.

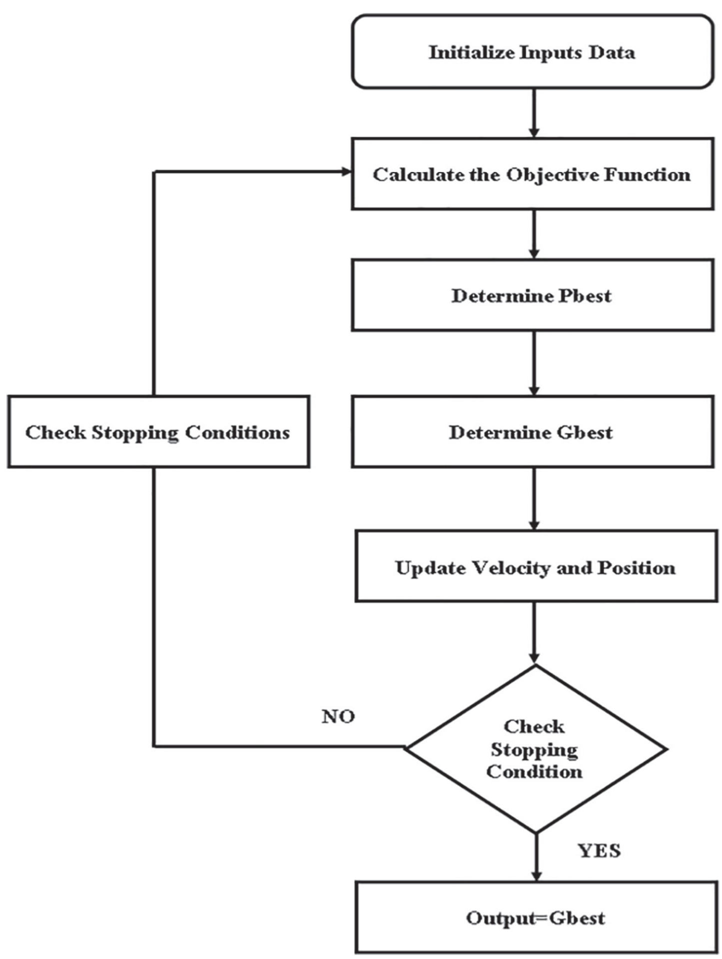

Figure 1: Flowchart of PSO

Literature Review

Author(s) & Year	Method / Technique	System / Case Study	Key Variables Controlled	Major Findings	Limitations
Asabere et al. (2025)	PSO-based DSTATCOM optimization	IEEE 33-bus radial system	DSTATCOM size & location	Active loss ↓58.8%, reactive loss ↓96.7%, voltage improved (0.817→0.99 p.u.)	Focused on single device; limited multi-device coordination
Xia et al. (2025)	Improved MOPSO with genetic mutation	IEEE 33 & 113-bus PV-integrated systems	PV inverters, OLTC, capacitor banks	Loss ↓40–44%, voltage deviation ↓~50%	Increased computational complexity
Wang et al. (2021)	Hybrid PSO-GA with adaptive operators	IEEE 33-bus system	OLTC, DG, ESS, capacitors	Improved voltage profile & convergence vs conventional methods	Algorithm tuning required
Chen et al. (2025)	Robust Deep Reinforcement Learning (RDRL)	13-, 123-, 8500-node systems	Smart inverters, OLTC	Stable voltage under uncertainty, reduced losses	High computational demand, real-time complexity
Sabere et al. (2023)	PSO-GSA hybrid optimization	IEEE 123-bus system	OLTC, VAr devices, ES, DR	Reduced losses, improved voltage, fewer tap operations	Multi-period complexity
Altuma et al. (2023)	Genetic Algorithm (GA)	Distribution network (general case)	OLTC taps, capacitor steps	Maintained voltage (0.95–1.05 p.u.), improved power factor	Limited scalability analysis
Ratra et al. (2025)	Fuzzy + Taguchi Method (TM)	Transmission/ distribution system	OLTC, VAR controllers	Loss ↓ (47.808→43.65 MW), improved L-index (0.3014→0.2491)	Less adaptive to dynamic systems
Singh et al. (2020)	Modified Moth Search Optimization (CMSO)	IEEE 33 & 118-bus systems	DERs, OLTC, capacitors	Reduced energy loss, improved voltage, lower DER requirement	Complexity in MINLP formulation
Xu et al. (2025)	Multi-Agent Reinforcement Learning (MARL)	IEEE 13 & 123-bus systems	Distributed control agents	Faster convergence, robust voltage control under uncertainty	Coordination complexity
Zhang et al. (2025)	NSDBO + MPC (two-stage optimization)	IEEE 33-node system	OLTC, CBs, SVCs	Loss ↓~59%, voltage deviation ↓~71%	Requires forecasting accuracy

Methodology

In this research two different optimization algorithms are tested under identical operating conditions their performance is compared using IEEE 33-Bus Distribution System. The system operates at 12.66kV, is first modeled in ETAP to perform load flow analysis and calculate baseline power losses and voltage variances.

These findings are then used as reference values for further optimization in MATLAB.

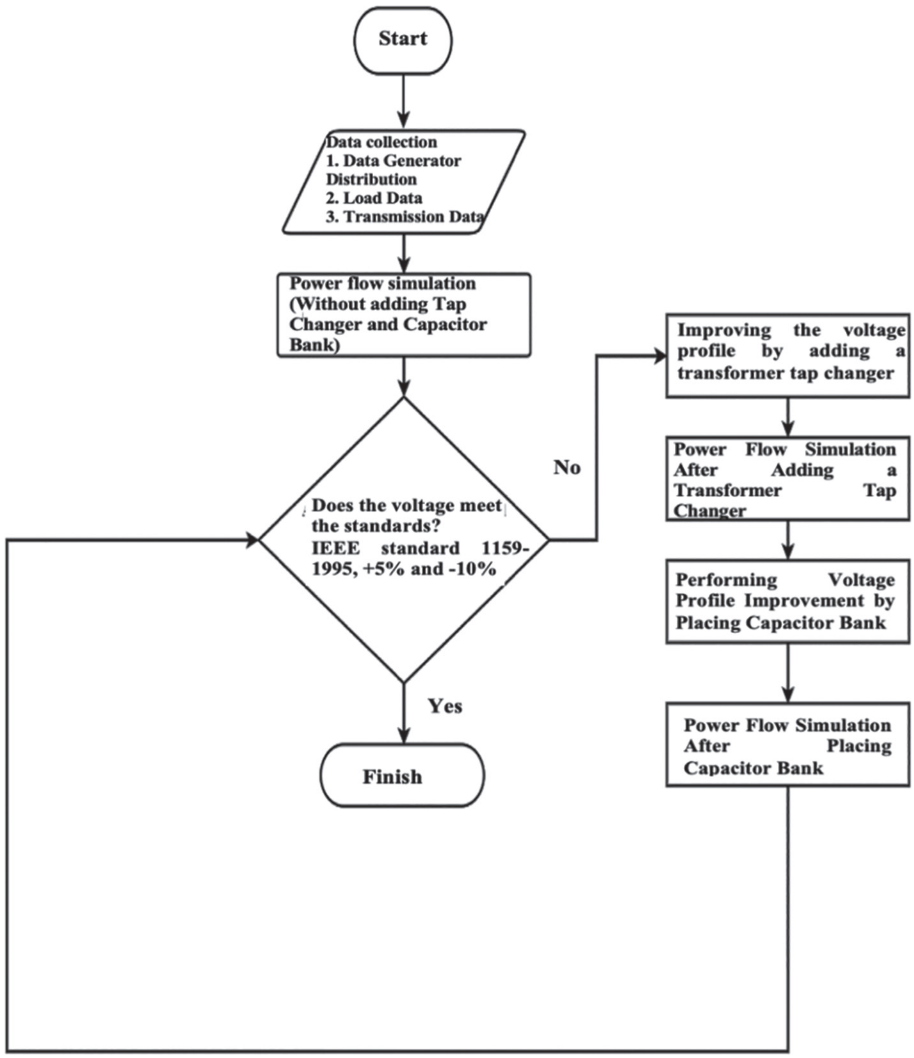

Figure 2: Research Flowchart

Using Genetic Algorithms (GA)Technique:

The ON-Load Tap changer (OLTCs) and capacitor banks coordinated Optimization process is carried out with the assistance of the Genetic Algorithm (GA).GA begins with the original population of the system configurations i.e. tap position and capacitor locations. The solutions are considered based on the fitness function that consider the compliances of voltage profile and loss minimization. Selection retains better performing solutions and the crossover and mutation processes are used probabilistically to search better configuration and maintain diversity during search.

This is analysed in a linear manner. The initial process involves testing the base case without compensation in order to be educated about the breach of voltages as well as high power loss. The capacitor banks are then independently connected to examine their impact on their voltage profile and lost reduction with the help of OLTCs to improve the voltage regulation. Finally, a coordinated approach is generated with the help of GA in order to interconnect the OLTCs and capacitor banks in a way that the optimal performance of the system can be achieved. Individual and combined compensation systems result are compared to assist in determining the most effective set-up by contrasting them on performance on the improvement of voltage stability and minimized losses.

3.1. IEEE 33 bus distribution network system power flow (Initial condition) under GA algorithm

In order to identify the baseline performance, the IEEE-33 Bus Distribution system is initially studied without tap changer and capacitor banks. The Newton-Rapson algorithm is used to calculate the load flow analysis of voltage profiles and system losses. The findings indicate that 21 buses had exceeded the± 5% voltage limits specified by the IEE Standard 1159-1995, and Bus 18 has the lowest voltage of 0.913p.u. because the line impedance and loads are high. The voltage curve under this condition is given in figure 3.

The total power flow within the system is 3.918MW, comprising of losses. Active and reactive power losses as depicted in table 2 stand at 202.7kW and 135.1Kvar respectively meaning that the compensation is necessary to enhance voltage stability and minimize losses.

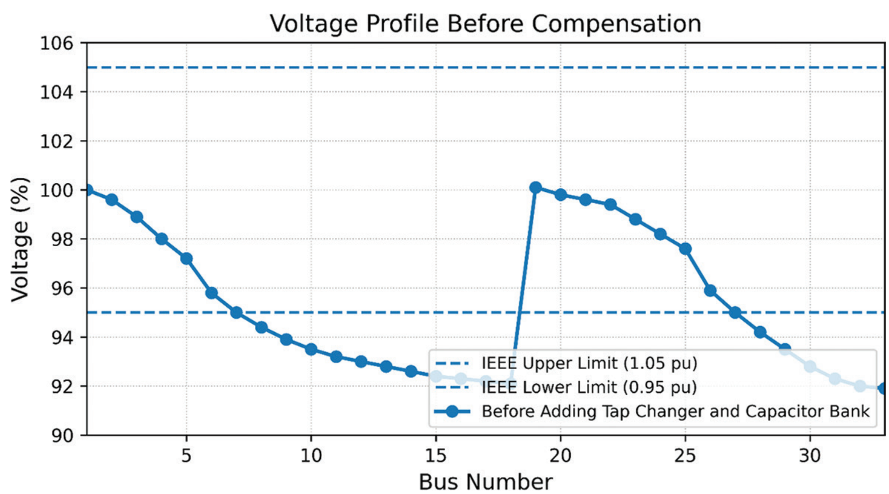

Figure 3: IEEE 33 bus voltage profile before adding tap changer and capacitor bank (initial condition) under GA algorithm

Table 2: Power flow results without adding tap changer and capacitor bank (initial condition)

Total Power Supplied		**Total Load Power**		**Power Loss Value**	
(MW)	**(Mvar)**	**(MW)**	**(Mvar)**	**(kW)**	**(kvar)**
3.918	2.435	3.715	2.300	202.7	135.1

3.2. Simulation results with the addition of Tap Changer under GA algorithm

In this stage, to reduce the voltage drops, two tap changer are added to the IEEE 33- Bus Distribution system. The tap changer is installed on Buses 5 and 8, according to optimization results. The updated voltage profile in Figure 4 shows considerable improvements in system performance. The number of buses that violets the permitted voltage limits has decreased from 21 to 17, illustrating the effectiveness of tap changer integration in voltage regulation. Therefore, Table 3 summarizes the power flow results obtained after installing the tap changers. Total system losses fall to 182.4kW and 130.3kvar when compared to base case, indicating an increase in overall efficiency. These findings show that, while tap changers improve voltage profiles and minimize losses, additional adjustment is requiring to optimize overall system.

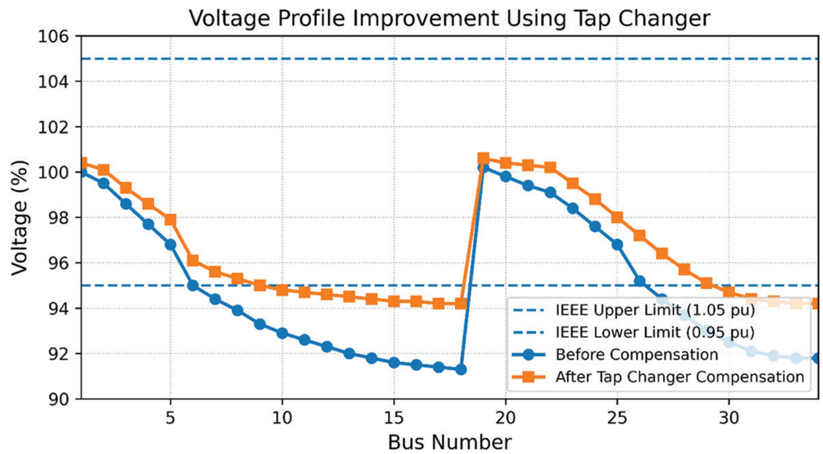

Figure 4: IEEE 33 bus voltage profile after adding Tap Changer under GA algorithm

Table 3: Power flow results with the addition of Tap Changer

Total Power Supplied		**Total Load Power**		**Power Loss Value**	
(MW)	**(Mvar)**	**(MW)**	**(Mvar)**	**(kW)**	**(kvar)**
3.987	2.430	3.715	2.300	182.4	130.3

3.3. Simulation results with the addition of Capacitor Bank under GA algorithm

The voltage enhancement was achieved with tap changers capacitor bank (2000kvar each) and their optimum placement in the IEEE-33 bus system with GA approach was used to enhance voltage stability and reduce losses. Bus 10 and bus 29 were identified to be the best location. The voltage profile becomes much better with integration of capacitor bank as shown in Figure 5, the count of buses with under voltage drops to 7, which is much more compliant with IEEE standard. Table 4 has the results of the power flow. The system provided a total power of 3.859MW and 0.562 Mvar to supply a load demand of 3.715MW and 2.300Mvar to give a loss of 143.8kW and 96.0kvar. Such data prove that the placement of capacitors banks is effective to enhance the voltage profile and minimize the losses of power.

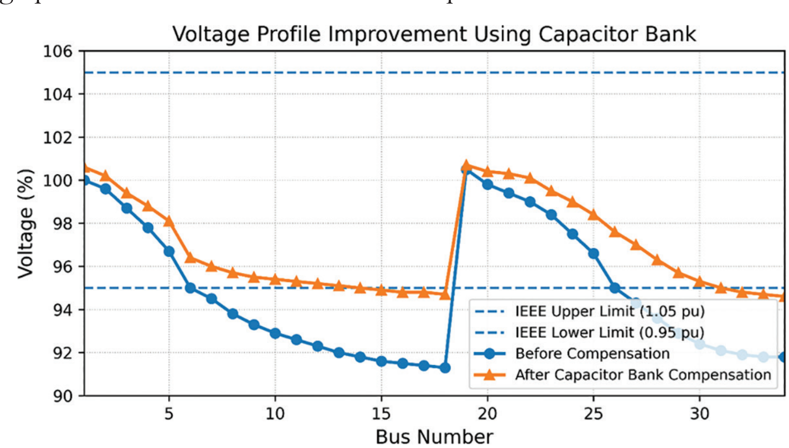

Figure 5: IEEE 33 bus voltage profile after adding Capacitor Bank under GA algorithm

Table 4: Power flow results with the addition of Capacitor Bank

Total Power Supplied		Total Load Power		Power Loss Value	
(MW)	**(Mvar)**	**(MW)**	**(Mvar)**	**(kW)**	**(kvar)**
3.859	0.562	3.715	2.300	143.8	96.0

3.4. Simulation results with the addition of Tap Changer and Capacitor Bank under GA algorithm

In order to achieve optimal voltage regulation and loss minimization, the tap changer and capacitor banks were coupled, and their combined impact was analyzed. The resulting voltage profile shown in figure 6, shows an improvement over individual implementation. The initial condition shows a voltage violates on 21 buses, however after combing them all buses run within IEEE 33 bus standard limits. The coordinated techniques outperform other methods for improving voltage profiles and reducing losses. The corresponding power flow are reported in table 5, which shows that system supplies 3.846MW and 0.536mvar to meet a load demand of 3.715MW and 2. 300Mvar.Total power losses are reduced to 130.7kW and 96.3kvar, demonstrating the effectiveness of the integrated optimization technique.

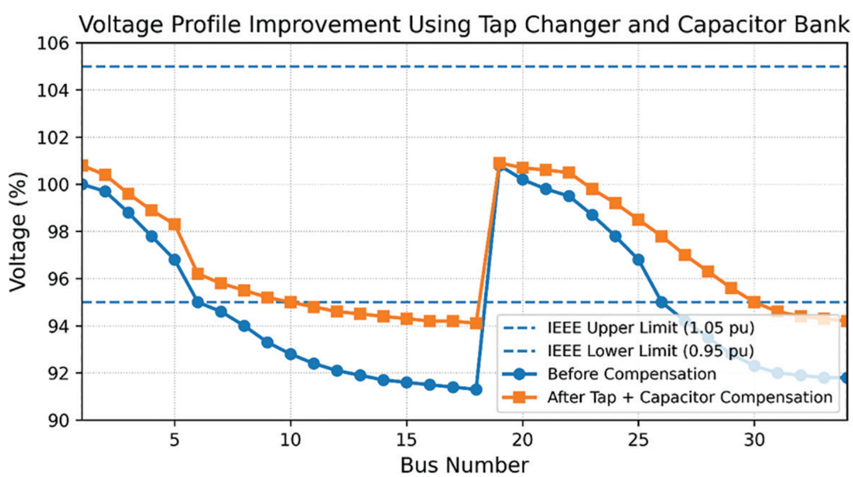

Figure 6: IEEE 33 bus voltage profile after adding Capacitor Bank under GA algorithm

Table 5: Power flow results with the addition of Capacitor Bank

Total Power Supplied		Total Load Power		Power Loss Value	
(MW)	**(Mvar)**	**(MW)**	**(Mvar)**	**(kW)**	**(kvar)**
3.846	0.536	3.715	2.300	130.7	96.3

3.5. Comparison results before addition and after addition of Tap Changer and Capacitor Bank under GA algorithm

The performance of several compensation strategies in the IEEE 33 Bus distribution system is compared in terms of voltages profile and power loss reduction, as shown in Figure 7. In the base situation,21 buses exceed or violates voltage limitation, resulting in losses of 202.7kw and 135.1kvar for total supply of 3. 918MW.Tap changer improves only four buses, whereas capacitor banks improve 14 buses while reducing losses significantly. However, combing both produces the best outcomes.

Coordinated compensation keeps all buses within acceptable voltage limits, reduces losses to 130.7kW and 93.3kvar, and reduces total supply to 3. 846MW.This demonstrate that the integrated approach is the most effective for improving voltage stability and minimizing losses.

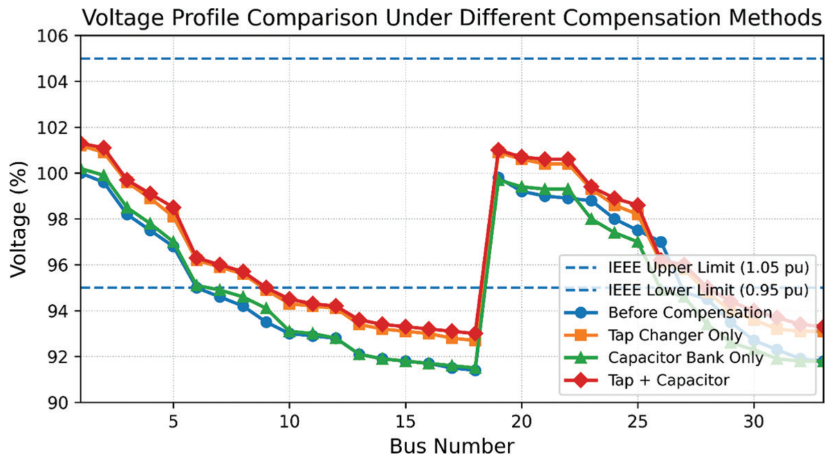

Figure 7: IEEE 33 bus voltage profile after adding Capacitor Bank

Using Particle Swarm Optimization Technique:

In this analysis, Particle Swarm optimization is used to optimize voltage profile improvement and power loss minimization in the IEEE 33 Bus Distribution through optimization of the slack bus tap changer and shunt capacitor placement. The system data are taken from the MATPOWER case33bw file, and power flow analysis is carried out using Newton-Rapson method using the runpf function.

A set of ten candidate's buses are chosen for capacitor placement, each having a maximum reactive power injection limit of 0.0005 p.u. The slack bus tap changer is modeled with discrete values of -1.25%,0%and +1.25%. To balance exploration and convergence, the PSO methods uses a swarm of ten particles over 100 iterations, with appropriate inertia and acceleration coefficients. The fitness function is formulated to reduce active power losses, voltage variance, and penalties for violating standard voltage limits.

3.6. IEEE 33 bus distribution network system power flow (Base System) under PSO algorithm

The base case voltage profile, given in Figure 8, shows severe voltage drops, especially at Buses 18 and 33, where voltage dip below 0.95 p.u. During optimization, particle position is updated using standard PSO equations with constraints on both tap settings and capacitor size. The optimization results show that there is voltage iregulation and high system losses in base case.

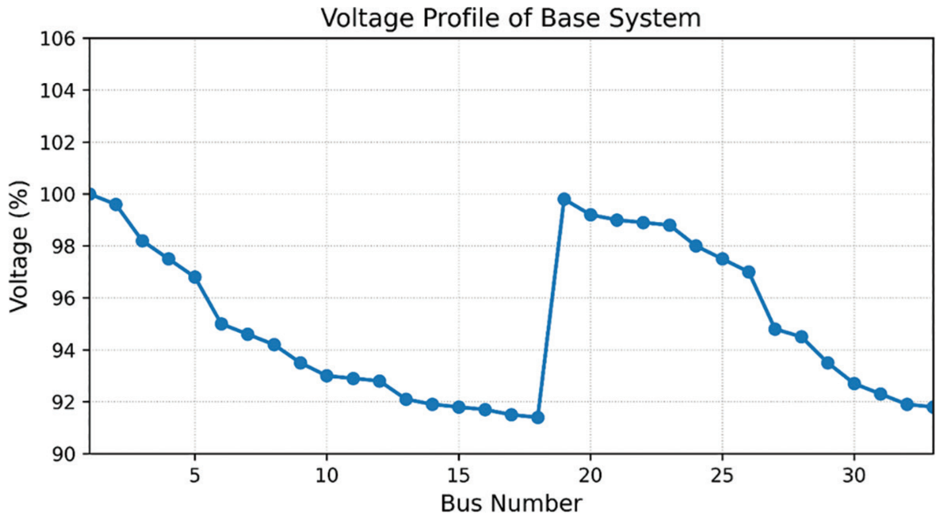

Figure 8: IEEE 33 bus voltage profile before adding tap changer and capacitor bank (initial condition) under PSO algorithm

3.7. Simulation results with the addition of Tap Changer under PSO algorithm

In this condition, the slack bus tap changer is optimized with discreate setting (-1.255,0%, and +1.25%) to adjust the feeder voltage level. AS shown in Figure 9 the sending end voltage at bus 1 rises to around 1.0125 p.u. Resulting upward shift of the entire voltage profile. However, due to the IEEE 33-BUS distribution Systems radial nature, the voltage drops along the feeder remain high. While upstream voltage improves, the tap changer alone cannot maintain acceptable voltage levels on downstream buses such as Buses 17 and 18, which remain below the 0.95 p.u. standard. This shows that tap changer operation alone cannot effectively address local reactive power deficits in the system.

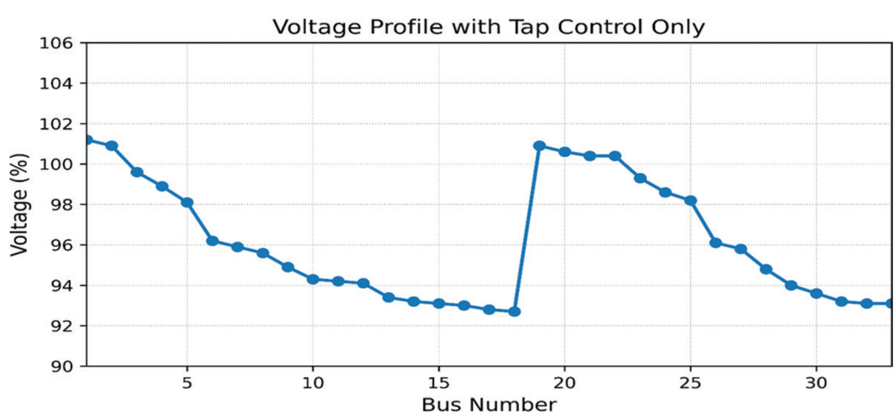

Figure 9: IEEE 33 bus voltage profile after adding Tap Changer under PSO algorithm

3.7. Simulation results with the addition of Capacitor Bank under PSO algorithm

In this condition, ten buses are equipped with shunt capacitor banks to offer localized reactive power assistance and lower line current. As shown in Figure 10, the voltage profile improves at capacitor position, resulting in a lower voltage drop along the feeder. When compared to tap changers, capacitor banks provide more targeted voltage support at certain busses. However, due to the small capacitor size (0.0005 p.u.) and the lack of global voltage control, some downstream buses remain close to or slightly below the 0.95 p.u. limit. This suggests that while capacitor banks can improve local voltage conditions, they may not fully provide adequate voltages levels throughout networks.

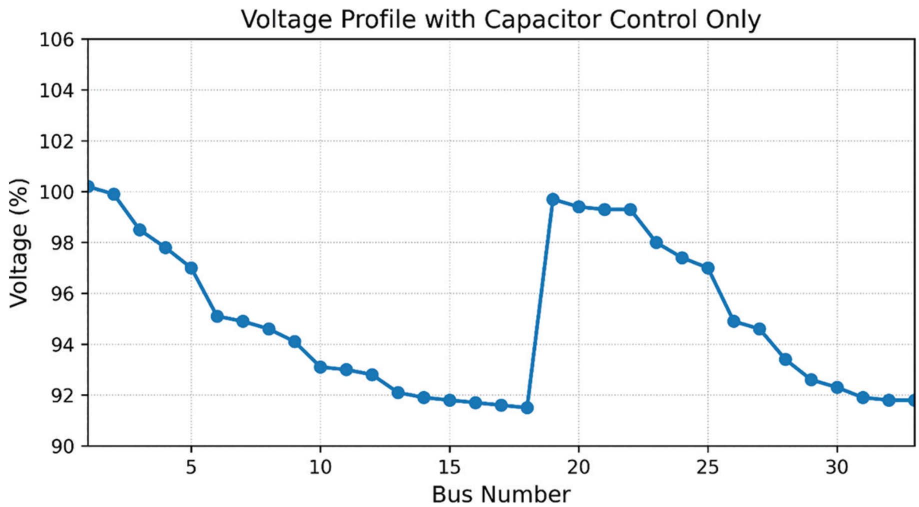

Figure 10: IEEE 33 bus voltage profile after adding Capacitor under PSO algorithm

3.8. Simulation results with the addition of Tap Changer and Capacitor Bank under PSO algorithm

The final scenario uses Particle Swarm Optimization (PSO) to coordinate discrete tap changer settings and continuous capacitor injections for optimal voltage control. The combined "Tap with Capacitor Profile" outperforms, with tap changer increasing the initial feeder voltage and capacitor providing localized reactive support to smooth the voltage drops as shown in Figure 11. As a results, all 33 buses meet the IEEE).95-1.05 p.u limitation while achieving the lowest active power loss through lower current flow and improved voltage regulation. Furthermore, in voltage dips at Buses 18 and 33 are decreased, demonstrates improved system stability and distribution network efficiency.

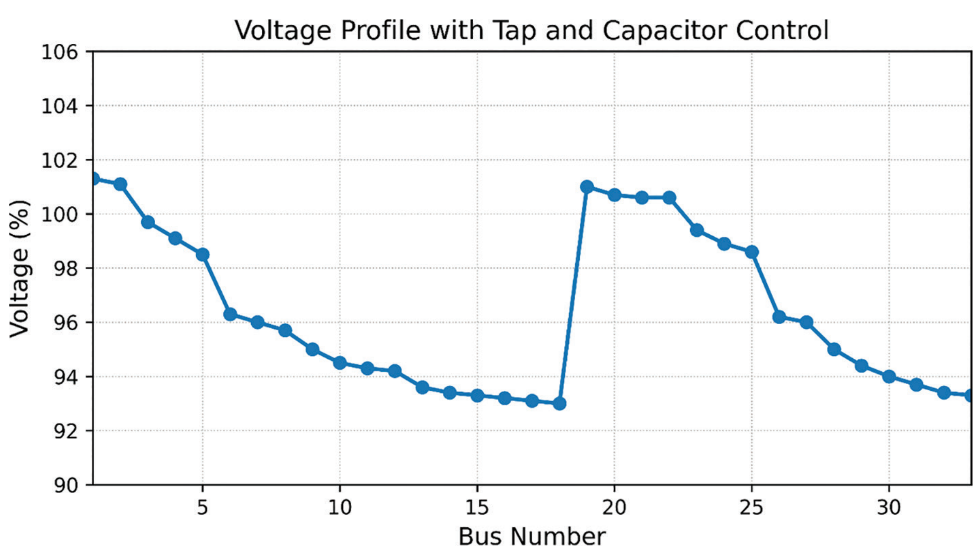

Figure 11: IEEE 33 bus voltage profile after adding Tap and Capacitor under PSO algorithm

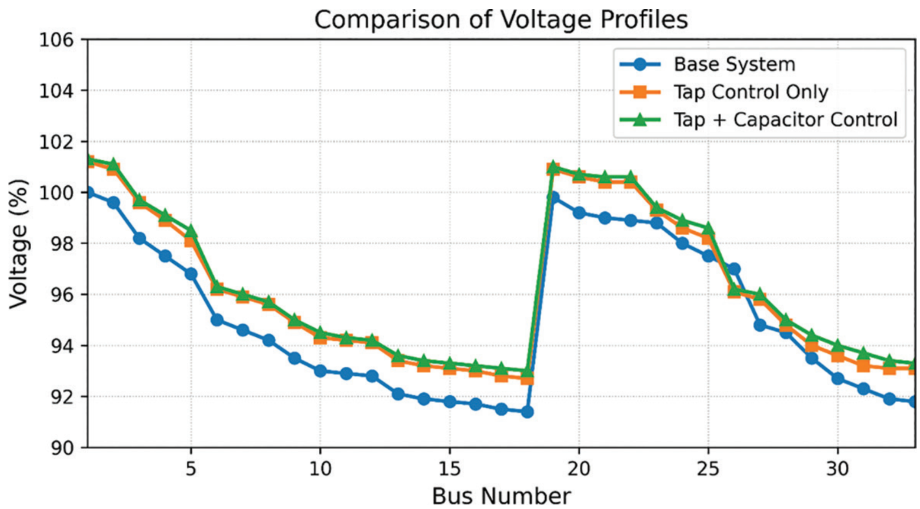

Figure 12: IEEE 33 bus voltage profile Comparisons of Base, Tap Control and Tap with Capacitor condition under PSO algorithm

Table 6: Performance Comparison Table of Base, Tap Only, Capacitor Only and Tap with Capacitor System

Case	Psup (MW)	Qsup (Mvar)	Pload (MW)	Qload (Mvar)	Ploss (kW)	Qloss (kVar)
Base System	3.918	2.435	3.715	2.3	202.7	135.1
Tap Only	3.912	2.431	3.175	2.3	196.9	131.3
Capacitor Only	3.915	2.388	3.715	2.255	200.1	133.4
Tap +Capacitor	3.909	2.385	3.715	2.255	194.5	129.6

Conclusion

IEEE 33-bus radial system has a very high performance degradation at base operating conditions, active and reactive losses of power and var are 202.7 kW and 135.1 kVar respectively. Minimum bus voltage is reduced to 0.9131 p. u (Bus 18) and 21 buses exceed IEEE voltage limits. A two-step coordinated optimization of two tap changers and two capacitor banks completely recovers all the bus voltages in the allowable 0.95-1.05 p.u range, with the minimum voltage now set to 0.9516 p.u. This plan eliminates active power losses of 72 kW (35.5%), and reactive power losses of 41.8 kVar (30.9 percent), cutting them to 130.7 kW, and 93.3 kVar, respectively. The Genetic Algorithm can find the best locations and capacities of the voltage control devices and it proves to be effective to mixed-integer reactive power coordination. These results indicate the effectiveness of the synchronized compensation compared to the isolated deployment and future studies into looped distributions to improve the resilience to voltages.

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